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Short Paper

Labeled Facets: New Surface Texture Dataset

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Abstract

Object detection, recognition, segmentation, and retrieval have been at the forefront of 2D and 3D computer vision for a long time and have been utilized to address various problems in interdisciplinary domains. The 3D domain has not received as much attention as the 2D domain in several of these fields, and texture analysis in 3D is one of the least investigated. In the literature, there are several classic methods for retrieving and classifying 3D textures; however, research on facet-wise texture classification and segmentation is sparse. Moreover, in recent years deep learning excels in computer vision; utilizing its capacity for 3D texture analysis could improve performance compared to classical approaches. However, the scarcity of 3D texture data makes it challenging to employ deep learning. This paper presents a labeled 3D dataset based on already existing 3D datasets that can be utilized for texture classification, segmentation, and detection. The textures in the dataset are varied, with a wide range of surface variations. The dataset provides 3D texture surfaces annotated at the facet level, as well as fundamental geometric attributes such as curvature and shape index that can be utilized directly for further analysis. Download link for the dataset `https://bit.ly/3wgSQgW`.

CCS Concepts

• ***Computing methodologies*** → ***Mesh geometry models; Mesh models;***

1. Introduction

Texture analysis is a branch of computer vision that employs texture patterns to segment, categorize, recognize, and retrieve similar-textured objects from databases [BTA*17, ABC04, HLW*20]. Understanding the texture of sculptures and artifacts can aid in the precise reconstruction of historic sites in interdisciplinary fields such as cultural heritage. In the 2D domain, several classical and deep learning-based algorithms for texture analysis have been developed; however, in the 3D domain, only a few approaches that can be directly applied to surfaces are available [SLL*21, BTB*18, GJFW22]. Recently, deep learning-based techniques have proved effective in 2D computer vision tasks [KSH12]; thus, many studies transform the 3D texture problem into the 2D domain in order to utilize the potential of deep learning algorithms and address the issues. However, the texture is a surface variation in a neighborhood with local features, and transforming from one domain to another could lead to the loss of fine details. We recognize that the lack of 3D texture data is a significant factor, and the availability of 3D texture data may enable texture analysis on 3D surfaces and the use of deep learning techniques.

As a result, we present a dataset containing surfaces from cultural heritage domains in addition to real-time objects. The primary objective of this dataset is to provide opportunities to investigate texture at the facet level, including classification and segmentation. The dataset is built from two existing datasets *SHREC'18* [BTB*18] and *Real-World Textured Things* [MPCT20] where the first dataset have heritage objects and the other has real-world objects. 3D surfaces for our dataset are cropped with varying proportions of texture and non-texture regions from these datasets. Currently, the dataset can be used to classify textures and non-textures at the facet level.

Outcomes and major contributions of the proposed work are as follows:

1. We prepare a 3D texture database named KU-3DTexture for facet level surface analysis.
2. We computed geometric properties at each facet along with the label, which can be utilized for texture classification, detection, and segmentation.
3. Classical and deep learning-based algorithms can be evaluated using the dataset.

2. Related datasets

SHREC'17 [BTA*17], *SHREC'18* [BTB*18], *SHREC'20* [LSL*20] and *SHREC'21* [SLL*21] are among the most used

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datasets for 3D texture analysis. *SHREC'17* consists of 15 subjects, each with 48 samples in three different resolutions, where the 3D surfaces only cover the texture region. This dataset is already preprocessed and constructed for tasks such as classification and retrieval where, each surface sample in the dataset represents a textured pattern as a whole. There will be no non-texture component present in the surface sample. *SHREC'18* comprises thirty surfaces with varied texture patterns, most of which have texture and non-texture regions. *SHREC'2020* is a riverbed sample collection of 256 surfaces from eight different classes. *SHREC'21* is comprised of 938 surfaces derived from eight distinct types of 3D scanned models of cultural heritage relics. *Real-World Textured Things* is another collection that includes real-world objects. However, it is not used in texture analysis. Since it has rich geometric texture patterns we utilized it to create our dataset. It contains 568 different 3D objects derived from real-world items.

3. Proposed Dataset

The dataset emphasizes the significance of the facet-level study of texture patterns on three-dimensional surfaces. For texture analysis, a dataset with facet-level labeling is required to train a system for classification, recognition, and segmentation tasks. This is one of the less researched fields, and one of the key reasons is a lack of datasets. A few datasets exist to classify a surface as a whole and retrieve surfaces based on a query surface; however, the research community lacks datasets with a labeled facet that enable facet-level analysis. As a result, we developed this dataset to aid texture analysis and benefit the scientific community. The *SHREC'18* and *Real-World Textured Things* datasets were used in the creation of the new dataset because they contain cultural artifacts and real-world objects with a variety of texture patterns. MeshLab [CCC*08] is used to meticulously crop 3D surfaces from objects in both datasets so that the majority of cropped surfaces have texture and non-texture regions that may be used for texture analysis. Furthermore, the collection also comprises surfaces with only textures and surfaces with only non-textures of simple and complex geometric patterns. Despite the fact that *Real-World Textured Things* contains 568 objects, we have carefully selected only a few of the 3D objects that has rich texture and non-texture patterns and We will investigate the remaining objects for the next version of the dataset. The dataset currently contains 3D surfaces that are cropped equally from both datasets, *SHREC'18* and *Real-World Textured Things*. Cropped surfaces are pre-processed to remove duplicate facets and vertices; non-manifold vertices and facets. Also, the orientations of facets are coherently aligned. The collection includes 89 samples, the largest of which has 785K vertices and 1.6 million facets and the smallest of which has 8K vertices and 16K facets. As a result, the dataset may be large enough to train both learning-based and classical algorithms for binary texture classification at the facet level on a 3D surface. Although the current version of the dataset is suitable for binary texture classification on 3D surfaces, a future version of the dataset may include multiple samples for each surface, which will be beneficial for training a multi-class network to categorize multiple texture patterns. The surfaces are in *.mat* format, with each file containing vertices, facets, facets ring, and computed features such as *curvedness* (C), *Gaussian curvature* (CG), *mean curvature* (CM), *local depth* (LD), *shape index* (SI), *azimuth* (AZ), and *elevation* (EL). Table 1 contains a summary of data annotation. In addition, a text file documenting the process of converting the dataset to *.npy* format is included so that it can be utilized in python programming environment. *SHREC'17* with a broad range of surfaces can be added as supplement with our dataset to evaluate algorithms. Since each surface in *SHREC'17* has textures alone, it may be best suited for testing any novel algorithm at the facet level classification.

4. Feature computation

Normal (x,y,z) is computed at each facet, and it is used to compute *azimuth* and *elevation* as $tan^{-1}(y,x)$ and $tan^{-1}(z,\sqrt{(x^2+y^2)})$, respectively. *Mean* and *Gaussian* curvatures are computed using [MDSB03]. The *shape index* (SI) is a curvature-based measure and is defined as $SI(P)=\frac{1}{2}-\frac{1}{\pi}tan^{-1}\frac{k_1(P)+k_2(P)}{k_1(P)-k_2(P)}$ where k_1 and k_2 are the maximum and minimum principal curvatures, and $k_1>k_2\ \forall P$. Formally, k_1 and k_2 are given as $k_1=H(P)+\sqrt{H^2(P)-K(P)}$ and $k_2=H(P)-\sqrt{H^2(P)-K(P)}$ where $H(P)$ and $K(P)$ are the mean and Gaussian curvatures at a point P. The *local depth* is calculated using a covariance matrix (H) constructed from neighbors $v_1,v_2\cdots v_n$ of a point P. The eigenvalues and eigenvectors of the matrix H are then computed, with the eigenvector corresponding to the least eigenvalue serving as the normal. Following that, a plane $Ax+By+Cz+D$ is built using the obtained normal and the vertices $v_1,v_2\cdots v_n$. Finally, the distance from a point to the plane is used to calculate the local depth. Another measure called curvedness, $C(P)$, which is also based on k_1 and k_2. Formally, $C(P)=\sqrt{\frac{k_1^2+k_2^2}{2}}$, where the value of $C(P)$ describes the nature of the surface at point P. The texture and non-textured regions are *labeled* as zero and one, respectively. Each facet has three vertices, therefore the feature computed at vertex level can be mapped to facet by taking average of the features of the three vertices.

5. Experimental analysis

Few samples are selected for quantitative and qualitative study of texture classification at the facet level based on the underlying geometric attributes obtained at each facet. Even though there are numerous techniques for texture analysis in the literature, such as ordered ring facets [WBDB14, WTBDB15a, WTBDB15b] and mesh convolution [TBOW21], we have classified texture and non-texture regions using basic geometric features.

5.1. Quantitative analysis

The metrics precision and recall are used to validate the performance of the derived features curvedness, mean curvature, Gaussian curvature, local depth, shape index, azimuth, and elevation. Experiments are carried out with individual and combination of these features, and the results are summarized in Tables 2 and 3. We used normalized values of each of these features as predicted scores, and compared with the actual labels to perform fundamental classification to verify the effectiveness of each feature. The result of individual features for binary texture classification on 3D surfaces are shown in Table 2, where each facet is classified as texture

Table 1: *Data annotation and computed features at the facet level.*

Field	Description	Size
azimuth_elevation ($\mathcal{F}_{\mathcal{AZ}}$)	Azimuth and elevation	$\mathcal{F}_{\mathcal{AZ}} \in \mathcal{R}^{M\times 2}$ where M is the number of faces
face ($\mathcal{F}$)	Facets	$\mathcal{F} \in \mathcal{R}^{M\times 3}$
facet_Cgauss ($\mathcal{F}_{\mathcal{GC}}$)	Gaussian curvature	$\mathcal{F}_{\mathcal{GC}} \in \mathcal{R}^{M\times 1}$
facet_Cmean ($\mathcal{F}_{\mathcal{MC}}$)	Mean curvature	$\mathcal{F}_{\mathcal{MC}} \in \mathcal{R}^{M\times 1}$
facet_Cur ($\mathcal{F}_{\mathcal{C}}$)	Curvedness	$\mathcal{F}_{\mathcal{C}} \in \mathcal{R}^{M\times 1}$
facet_label ($\mathcal{F}_{\mathcal{L}}$)	Labels for each facet	$\mathcal{F}_{\mathcal{L}} \in \mathcal{R}^{M\times 1}$
facet_localdepth ($\mathcal{F}_{\mathcal{LD}}$)	Local depth	$\mathcal{F}_{\mathcal{LD}} \in \mathcal{R}^{M\times 1}$
facet_shapeIndex ($\mathcal{F}_{\mathcal{SI}}$)	Shape Index	$\mathcal{F}_{\mathcal{SI}} \in \mathcal{R}^{M\times 1}$
fring ($\mathcal{F}_{\mathcal{R}}$)	Cell array of adjacent facets of each facet	$\mathcal{F}_{\mathcal{R}} \in \mathcal{R}^{M\times(1\times 3)}$
vertex ($\mathcal{V}$)	Vertices	$\mathcal{V} \in \mathcal{R}^{N\times 3}$ where N is the number of vertices

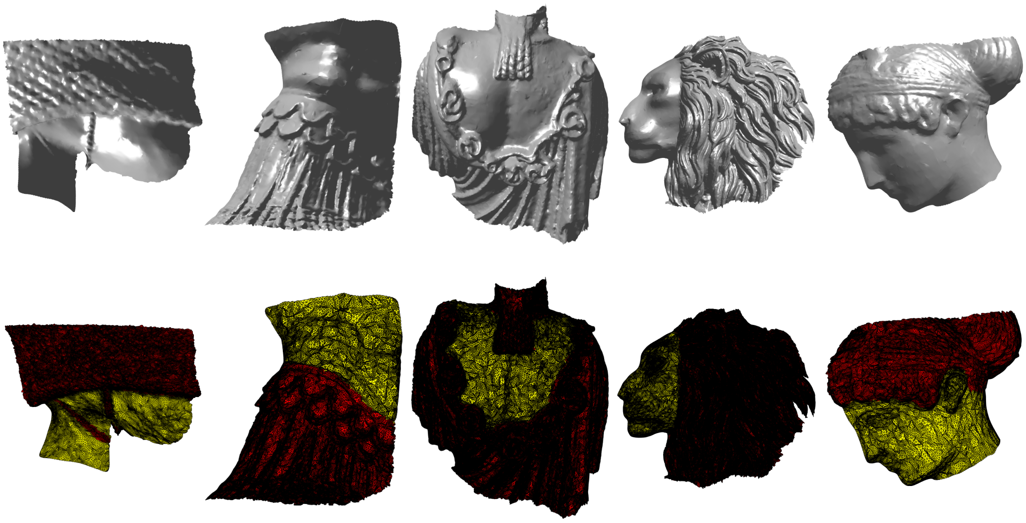

Figure 1: *A few examples of surfaces with annotated ground truth, with yellow representing the non-textured region and red representing the texture region.*

or non-textured. *SI* and *CG* have demonstrated the best classification performance; however, the other features *LD*, *EL* and *AZ* have also demonstrated consistent performance. We have also conducted experiments using combinations of two features; the results are summarized in Table 3. As expected, since *SI*, *CG*, and *LD* performed better as individual features, the combinations of these features *LD* and *SI*, *CG* and *LD* performed the best. The second-best performance has been shown by the combinations of *LD* and *CM*, and *LD* and *EL*. A thorough experiment using linear combinations of multiple features is required to find the best combination. However, through experimentation we observed that as compared to individual features, combination of two features does not show much improvement.

5.2. Qualitative analysis

The surface samples are visually shown to highlight how the derived features distinguish between textured and non-textured regions, individually and in combination. The *SI* and *CG* features have the best quantitative performance; nevertheless, qualitative analysis reveals that they do not distinguish between texture and non-texture regions. Even though *LD* and *CM* have demonstrated the second-best performance quantitatively, they visually distinguish between the texture and non-texture regions. Similarly, the features *EL*, *SI*, *CM* in combination with *LD* have exhibited enhanced distinction between textured and non-textured surface regions.

6. Conclusions

We presented a dataset for 3D texture analysis with facet annotation, and the dataset in its current form can be used for texture and non-textured classification. We computed geometric features at each facet in addition to the facet label. This dataset could aid researchers in texture identification, classification, and segmentation. We intend to expand the collection in the future to include multi-class texture patterns.

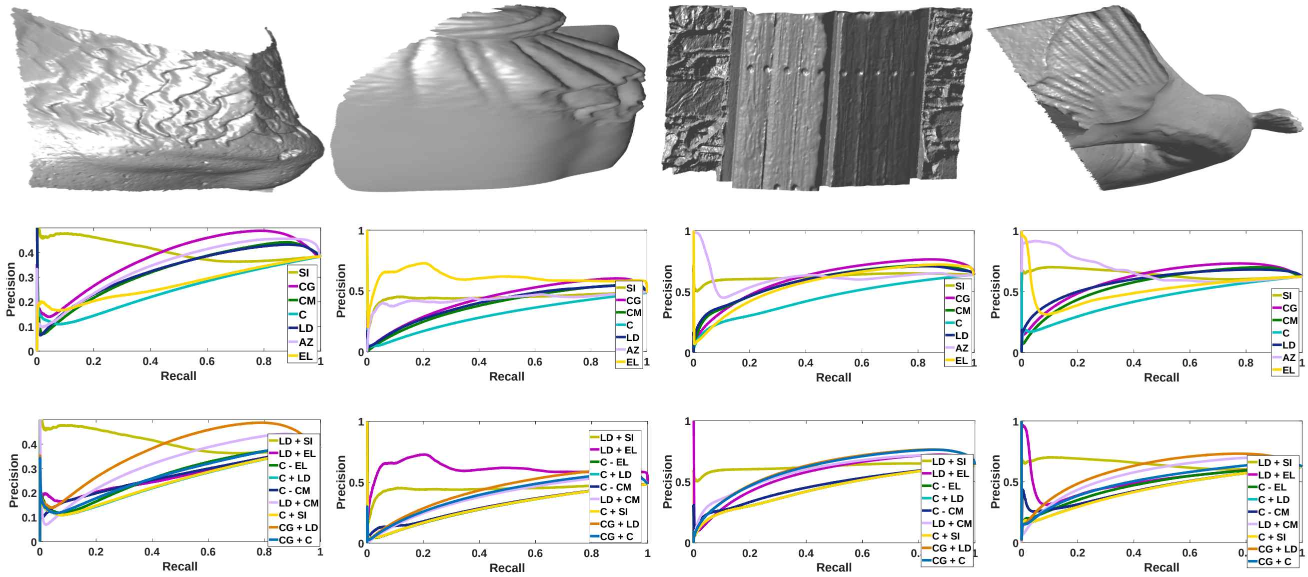

Figure 2: *Computed features used in a quantitative study of facet level texture classification of four surfaces from the dataset. The top row shows the original images, the middle row shows the precision and recall for individual features, and the bottom row shows the precision and recall for combinations of two derived features.*

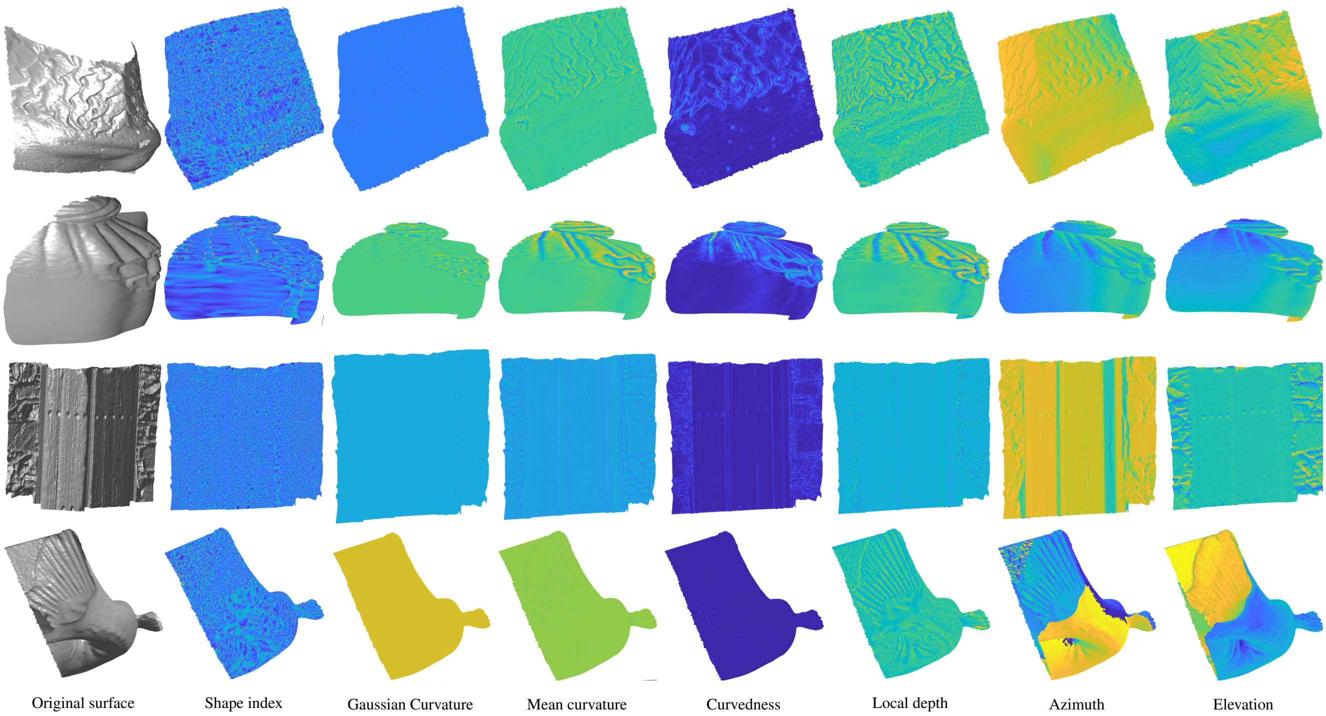

Figure 3: *A few visual examples of surfaces with computed features at each facet. Original surface, shape index (SI), Gaussian curvature (CG), mean curvature (MC), curvedness (C), local depth (LD), azimuth (AZ), and elevation (EL) are shown from left to right.*

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Table 2: *Facet level classification of texture and non-texture regions for four randomly selected 3D surfaces from our dataset using individual features. The top performance is highlighted in blue, while the second best performance is marked in bold.*

Data	Precision							Recall						
	SI	CG	CM	C	LD	AZ	EL	SI	CG	CM	C	LD	AZ	EL
Surface-1	0.451	**0.353**	0.286	0.186	0.291	0.312	0.239	**0.500**	0.536	0.466	0.298	0.471	**0.500**	0.357
Surface-2	**0.444**	0.371	0.301	0.181	0.338	0.427	0.593	0.475	**0.498**	0.433	0.271	0.458	0.466	0.594
Surface-3	0.622	0.567	0.552	0.362	0.558	**0.612**	0.505	0.498	0.527	**0.504**	0.360	0.501	0.483	0.489
Surface-4	**0.642**	0.568	0.510	0.362	0.564	0.666	0.494	0.500	0.526	0.494	0.361	**0.507**	0.493	0.426

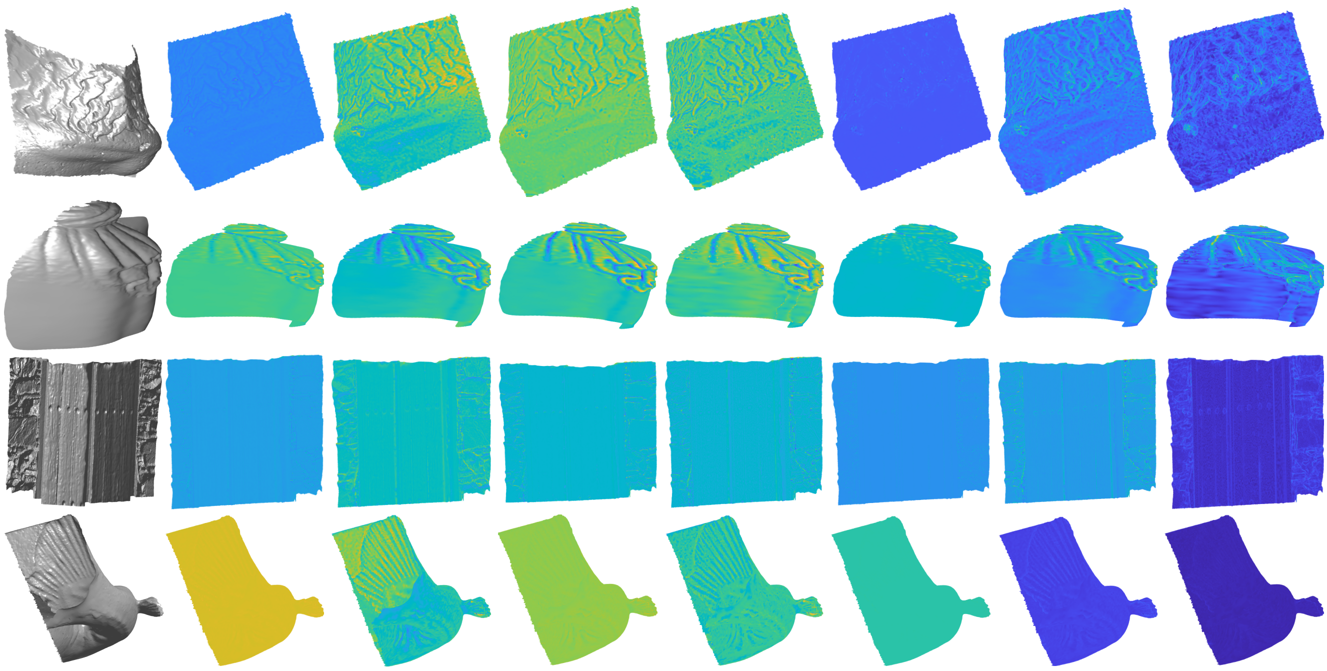

Figure 4: *A few examples of 3D surfaces from our dataset shown with a different combination of computed features. Original surface, local depth + Gaussian curvature (LD + CG), local depth + elevation (LD + EL), local depth + mean curvature (LD + CM), shape index + local depth (SI + LD), curvedness + Gaussian curvature (C + CG), local depth + curvedness (LD + C), and curvedness + shape index (C + SI) are shown from left to right.*

Table 3: *Facet level classification of texture and non-texture regions of four randomly selected 3D surfaces from our dataset using combination of two computed feature. The best performance is in blue, while the second best performance is in bold.*

Data	Precision									Recall								
	LD + SI	LD + EL	C - EL	C + LD	C - CM	LD + CM	C + SI	CG + LD	CG + C	LD + SI	LD + EL	C - EL	C + LD	C - CM	LD + CM	C + SI	CG + LD	CG + C
Surface-1	0.405	0.239	0.231	0.186	0.232	0.285	0.189	**0.352**	0.235	**0.499**	0.357	0.373	0.297	0.359	0.466	0.302	0.534	0.379
Surface-2	**0.444**	0.593	0.176	0.181	0.226	0.300	0.181	0.371	0.333	0.475	0.594	0.266	0.271	0.305	0.433	0.271	**0.498**	0.460
Surface-3	0.622	0.505	0.362	0.362	0.404	0.551	0.362	**0.567**	0.562	0.498	0.489	0.360	0.360	0.385	0.504	0.360	0.527	**0.524**
Surface-4	**0.643**	0.494	0.424	0.362	0.401	0.510	0.361	**0.568**	0.460	**0.500**	0.426	0.409	0.361	0.374	0.494	0.361	**0.526**	0.447

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